Digital Downloads and the Prohibition of Resale Markets for Information Goods

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Abstract

An existing theoretical literature finds that resale markets cannot reduce profits for perfect durable monopolists. If the model is relaxed to allow consumers to tire of goods, resale markets may prevent firms from maintaining high market prices resulting in lower profits. I investigate empirically the welfare effects of curtailing resale in the video game market, one of the industries that can soon legally prevent resale by distributing products solely as digital downloads from places like iTunes, Kindle Store, and PlayStation Network. I first estimate a dynamic model of demand for video games in a market with allowed resale using data on new and used video game sales. I then use the estimated parameters to simulate purchase behavior, optimal prices, and welfare under prohibited resale. I find that when resale is allowed, firms are unable to maintain high market prices for their goods because used goods satisfy residual demand. The ability to do so when resale is prohibited yields significant profit increases.

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1 Introduction

A common implication of theoretical models of perfectly durable products is that resale markets do not reduce producer profits. But in some information good industries practitioners vehemently disagree. For example, Phil Harrison, president of Atari, stated that "...there’s no doubt that second-hand game sales have a macro-economic impact on the [video game] industry and a lot of people get miserable about it." While practitioners may be mistaken about the effects of resale, it is also possible that this discrepancy in viewpoint arises because existing theory does not allow for an important characteristic of these products. Many information products like video games, movies, books and language learning software have the feature that consumers lower their valuation with use, either because they tire of the products or learn the contained information. This feature has large implications for the effect of resale markets on profits and may help explain the practitioners’ view. In this paper, I investigate empirically the impact of allowed resale in the market for one category of information goods, video games. I find that resale markets substantially reduce firm profits, suggesting that firms have the incentive to utilize technological advances that allow them to legally prevent resale of their products.

In the canonical model of resale markets, where consumers do not tire of products with use, the typical finding is that resale markets can increase, but not lower, firm profits (Hendel and Lizzeri, 1999; Rust, 1986). The reasoning behind this finding is that forward-looking consumers incorporate future resale opportunities into initial willingness to pay, and as a result firm revenue should not be negatively impacted by resale markets. Since the firm typically produces fewer products and hence has lower total production costs when resale markets exist, this implies that resale markets may increase firm profits. While a minority of the papers that allow for imperfect durability, i.e. quality depreciation that for example occurs in cars, find that resale can harm firm profits, these papers still find that resale markets do not lower producer profits for perfectly durable goods. For goods that are perfectly durable, such as information goods, the existing theoretical literature unanimously concludes that resale markets do not lower producer profits. The empirical literature mostly follows the theoretical and does not allow consumers to tire with use. The one exception is

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1 Reisinger (2008).
2 Bulow (1982), Hendel and Lizzeri (1999), and Rust (1986) show that imperfect durability on its own may lower profits, because owners have the option of keeping a good they purchased earlier rather than returning to the market to buy a new product.
3 Ghose, Telang and Krishnan (2005), do allow for consumers to tire of goods in a supply chain model.
5 Resale can lower firm profit if resale transaction costs exceed primary market transaction costs.
6 (Anderson and Ginsburgh, 1994; Ghose, Telang, and Krishnan, 2005; Miller, 1974).
a concurrent working paper looking at the impact of resale of video games in Japan using a stockpiling model (Ishihara, 2011).

A simple example shows that when we relax the assumption of the canonical model and allow users to tire of products, resale markets can lower producer profits even for goods that are perfectly durable. Suppose the market is comprised of two equally-sized groups of individuals, denoted A and B, and that group-A individuals value initial use of the product at $12, and group-B individuals value it at $4. I assume further that the good’s quality does not depreciate over time, i.e. that it is perfectly durable. Despite the fact that the product’s quality does not decline over time, both types lower their valuation for a second period of use by 75%, and have zero value for a third period of use. I also assume that the monopolist producer of the good commits to prices ex-ante, and faces a negligible marginal cost. These assumptions mimic traits common among information products. For simplicity, I also assume that resale can only occur in the period directly after first sales occur.

In this example, the firm’s optimal price strategy depends heavily on whether or not resale is prohibited. If it is prohibited, the firm’s optimal strategy is to charge $15 in all periods. Under this strategy, the good is only sold to group-A individuals, who value two periods of use at $12 (1st use) + $3 (2nd use) = $15. Profits are $15 * size (group-A). Lowering the price over time to attract type B consumers is suboptimal, because if type A consumers know they can buy the product for less later, they will not be willing to pay as much. Alternatively, if resale is allowed, first period buyers can choose whether or not to sell in the second period. Suppose only group-A individuals buy in the first period. In the second period, if an A-type keeps the product, she receives $3 worth of utility from second use. Alternatively, she could sell to a group-B individual who values two periods of use at $4 + $1 = $5. Assuming an egalitarian bargaining solution, the secondhand market price would be $4. Since the second period yields $4 under resale rather than $3 worth of use when resale is prohibited, group-A individuals have a higher value for owning in the first period when resale is allowed. But resale also introduces an incentive compatibility constraint, since group-A individuals have the option of not buying the product in the first period and buying it for $4 in the second, for net utility equal to $11 ($12 (1st use) + $3 (2nd use) - $4 (2nd period price)). As a result, the highest price the firm can charge in the first period while still selling to group-A individuals is $5 ($12 (1st use) + $4 (2nd resale price) - $5 (1st period price) = $11 (utility from waiting to 2nd period)), given that resale occurs in the period following first sales. One can verify that the firm’s optimal strategy is to charge $5 in the 1st period, yielding profits equal to $5 * size (A), i.e. two thirds less than when resale was not allowed.

The intuition behind why resale of perfectly durable goods only reduces profits when
consumers tire of products is as follows. When goods decline in value to owners with use, residual demand is eventually satisfied with used goods at a price under the price charged in the first period. Consumers will anticipate the lower price in later periods and will not be willing to pay as much in earlier periods, limiting the firm’s power. By contrast, if consumers did not tire of the product, then in the example above group-A individuals would value the product higher than group-B individuals regardless of length of ownership, and there would be no gains to trade in the used market. In this case, allowed resale would not harm firm profits.

Tiring of products with use is an important feature of many information good markets. Take for example the video game market. Many consumers routinely buy and then resell games months later, after they have completed the game, accomplished the goals, grown tired of the multi-player functionality, etc. Many stores, such as Gamestop (which owns EB Games), Bestbuy, Amazon, and eBay, earn hefty profits from used games sales. For example, due to the high markup on used games, Gamestop earns more in profits from selling used games than from selling new ones.\(^7\)

A few statistics verify that, in the market for video games, used sales are substantial. Fifteen percent of video game expenditures are for used games, and the percent of used game transactions is likely much higher, since used game transactions tend to occur later in a game’s life cycle when market prices are lower.\(^8\) The data in this paper show that a game is resold nearly 0.2 times on average by the end of the first year following release, and 0.6 times by the three year mark.

Resale markets are currently protected by U.S. law, but technological advances will soon allow firms to extinguish resale markets legally. While the first-sale doctrine (17 U.S.C. section 109) gives owners the right to resell goods, even if they are copyrighted, the doctrine only applies to the original copy and therefore does not cover downloaded goods.\(^9\) To resell a downloaded good, one would need to sell the hard drive that contains it.\(^10\) In many cases, this would mean selling the entire device, along with all other information goods downloaded

\(^7\)See Kane and Bustillo (2009).


\(^9\)The first-sale doctrine dates back to an 1854 Supreme Court case, Stevens v. Royal Gladding, which ruled that a cartographer’s right to sole distribution ended at first sale. It was subsequently codified in 1909, and updated in 1976. In the Balance Act of 2003, Congress considered instituting a digital first-sale doctrine, allowing resale of digital goods via the "forward and delete" resale method. However, the bill did not pass. It has been unclear whether the first-sale doctrine applies to licensed goods. A District Court judge decided in Vernor v. Autodesk in 2008 that permanent licenses constituted sales, and as a result were covered by the first-sale doctrine. In September 2010, the Ninth Circuit Court of Appeals reversed this ruling, determining that firms can legally prohibit resale in their licensing agreement even if they never intended for the good to be returned to them.

to it. Hence, firms can effectively eliminate information goods’ resale markets by distributing such products solely through the download channel.\footnote{Firms can enforce this with access control software, and following the Digital Millennium Copyright Act (1998) can prosecute creators of software designed to circumvent such software.}

Technological changes that enable firms to prohibit resale are arriving quickly. Today, one can buy books on a Kindle or iPad, download mainstream video games through Direct2Drive or the PlayStation Network, download games to an iPhone, download movies and TV shows through Apple TV, or buy music through iTunes. Moreover, the share of sales that are digital has been increasing. For example, digital sales now outnumber physical sales for PC based video games, and Amazon announced that they sell more copies of books in digital form for the Kindle than they sell in hardcover.\footnote{See Whitney (2010), and Galante (2010).}

It is important to understand the effects of shutting down resale markets for information goods that consumers tire of. The impact could be large, since the four major entertainment industries (books, video games, movies, and music) together yield annual sales of around $90 billion in the US.\footnote{See Rich (2009), Hurt (2009), Digital Entertainment Group’s “Digital Entertainment Group Year-End 2008 Home Entertainment Sales Figures,” and the International Federation of the Phonographic Industry’s “Recorded Music Sales 2008” report.}

The most obvious question is what effect resale markets have on consumer and producer welfare. The existing theory shows that resale markets either have no effect or raise profits for producers of perfectly durable goods. However, my example above shows that when individuals tire of products, it is possible that resale markets reduce profits. Therefore, whether resale markets raise or lower profits of information product producers is an empirical question. Similarly, I found via simulations that, after accounting for the firm’s response, resale markets may raise or lower consumer welfare. Hence, the effects of resale markets on welfare is an empirical question.

To answer these questions, I employ a two-step approach. I first estimate demand parameters in a market where resale exists, using a dynamic discrete choice structural model of the consumer’s purchase and resale decisions and a dataset containing new and used sales of video games. Key parameters recovered in estimation determine the extent to which consumers tire of products and the heterogeneity in valuations for products. These parameters are identified by the timing of purchases and resales, and the price path. Next, using these estimated parameters, I can determine the effect of resale markets on equilibrium price paths. I find that resale markets put strong downward pressure on price - the elasticity of demand for new goods is far higher when resale is allowed, and the used good supply unilaterally drives down price.
In counterfactual analyses, under the assumption that firms can commit to quantities ex-ante, I find that prohibiting resale raises firm profits substantially, vindicating practitioners’ views. This result is due to the fact that price declines substantially over time when resale is allowed. When it is not, I find that the firm’s optimal strategy is to maintain high prices.

In the next section, I describe the data. Then, in sections 3 and 4, I detail the model of consumer demand and the supply side restriction, and then explain the estimation strategy. In section 5, I present the estimation results. In section 6, I analyze the impact of resale markets on price and present the counterfactual simulation results. I then conclude, and discuss broader issues.

2 Data

The data used in this paper are assembled by combining data from two sources. The first dataset, from the NPD group, provides information on total new sales of XBOX 360 video games in the U.S.\(^{14}\) The data on used sales come from a popular online auction marketplace, and thus comprise only a share of the market. Before combining the data, the used sales data are scaled up by a factor of approximately forty, in order to approximate the entire secondhand market.\(^{15,16}\) To my knowledge, these data are the most detailed to date for durable goods that consumers tire of with use. Therefore, even basic summary statistics may of be of interest themselves.

The resulting dataset contains monthly time-varying and time-invariant variables for each XBOX 360 game from the time the XBOX 360 platform was first released in November 2005 through December 2008. Time-varying variables are quantities sold and average prices of new and used games. Total purchases of a game in a period are constructed by summing new and used sales. Time-invariant variables include the games’ composite critic review scores, genres, ESRB ratings, and publishers from the NPD group and the "replay value" scores from Game Informer Magazine’s reviews for a subset of games. This last variable has five values, ranging from "Low - you’ll quit playing before you complete the game" to "High - you’ll still be popping this game in five years from now."

The trends in the price data, shown in Table 1, suggest that the decisions of when to buy

\(^{14}\)NPD observes over 80% of point of sales transactions of video games and scales them up to the market.

\(^{15}\)To scale them up, I employ the fact that 4% of sales in the first two months at GameStop, a national video game retailer, are used games (Kim, 2009). I assume that this holds for the market generally, and that the used data’s share of the used market is steady. With these assumptions, the appropriate scale-up factor \(\omega\) is given by: \(\omega = \frac{(Q_{\text{new}, NPD}^{2-\text{month}} + Q_{\text{used}, \text{raw}}^{2-\text{month}})}{25 + Q_{\text{used}, \text{raw}}^{2-\text{month}}}\).

\(^{16}\)This method of scaling used sales data has previously been used in Leslie and Sorensen’s (\()\).
and when to sell are non-trivial. If consumers buy a game right after it is released, they typically pay about $55 for the game. But, if they wait to buy the game, they can acquire the game for much less, since the price typically declines rapidly. They can on average save 20% by waiting 6 months, and about 50% by waiting a full year to buy the game. The implied rental prices (the buying price minus the amount received when reselling later) also typically decline over time. Thus, since both prices and implied rental prices decline over time, consumers must trade off between buying and using the product immediately and buying later at a lower price.

The sales data, also summarized in Table 1, show that sales are more front-loaded than in the classic diffusion model, in which sales start slow and increase over time. This front-loading may be due to the firm’s response to competition from used sales. In the market for video games, about 40% of total sales of a game in the first year occur in the first two months, on average. Not surprisingly, almost all of these games are new, and the firm profits from these sales. As time progresses, while total sales typically decline, the number of used sales initially increases, reaching a peak in the fifth month, and thereafter declines slightly before appearing to plateau. Since new sales continue to decline, the relative proportion of game sales that are of used games increases over time. By the end of the first year, monthly used sales account for over 40% of per month sales of a game. Hence, later on, the firm faces steep competition from used goods.

The cumulative sales of used games, relative to cumulative new games sales, also suggest used sales are an important component of this market. This is evident in Figure 1 which plots the ratio of cumulative quantity used to cumulative quantity new for each game as of the last period in the data against game age at that time (in the last period). This plot suggests that in the first few months of a game’s release, used sales are a very small fraction of total sales. But, by the end of the first year, cumulative used sales equal nearly 20% of cumulative new sales, and by the three year mark they equal 60% of cumulative new sales. This implies that three years after a game is released, each new game is resold 0.6 times on average. The mere frequency at which games are resold suggests used sales are an important feature of this market.

The importance of the used market seems to vary across games. Figure 1 shows that the fraction of cumulative sales that are used varies substantially after controlling for game age. At first glance, one might think that sampling error in the used game data explains this variation. Specifically, it is possible that each seller randomly decides whether to resell the game online or in store, and hence the fraction selling online as opposed to in a brick and mortar store is random, explaining the variation around the fitted line in Figure 1. To test this, I first regress the ratio of cumulative used to cumulative new sales on game
age indicator variables and record the residuals. If sampling error explains this variation, then the magnitude of the residual should decline in expectation with the total number of sales. In Figure 2, I show a box plot of the absolute value of these residuals over deciles of cumulative new sales of the game. This figure shows that there is no apparent pattern between the size of the sample and the absolute value of the residual. Hence, sampling error cannot explain variation in used game sales relative to new game sales.

While the data suggest that there is variation across games in the frequency in which they are resold, no game characteristic is a significant predictor, including, surprisingly, the "replay value" score. To demonstrate this, I regress the ratio of cumulative used to new sales on game age and several measures hypothesized to impact used game sales. The results are shown in Table 2. Unsurprisingly, the coefficient on game age is large and significant. However, none of the other variables are significant at the 5% level.

It is difficult to determine the exact reason why observables do not predict used sales with reduced form analyses. It could be that consumers tire of different games at different rates, and the rates are uncorrelated with any observable. Alternatively, the lack of explanatory power of the "replay value" score may be due to the fact that the data reflect equilibrium outcomes, and are difficult to measure using simple regressions.

As with many other entertainment goods, video game sales exhibit obvious seasonality. Using a similar model, Gowrisankaran and Rysman (2009) find that deseasoning the data prior to estimation yields similar parameter estimates to the method of including dummy variables. Since it is computationally much simpler, I opt for the former approach. Additional details are provided in Appendix C.

3 Model

In this section, I explain the demand side model and present a limited supply side model which is used only to implement an optimal price level constraint in the estimation procedure. Details are provided in subsections below.

3.1 Demand

The model of consumer demand is cast as a discrete choice problem, where at the beginning of each period each consumer decides whether to be an owner of each game, independent of which other games they own. If, at the beginning of a time period, they do not own the product in question, this framework requires that they decide between buying and not buying the product that period. If they do own the product, they alternatively decide between
keeping the product and selling it. If they buy or keep the product, at the beginning of the period, they receive full flow utility from using the game. If they wait to buy or sell the product, they receive no flow utility from the game.

This setup implicitly makes several assumptions. First, it assumes consumers do not have use for more than one copy of a particular game. This seems reasonable given that the second copy does not provide any additional functionality. Second, this framework implies that games are not substitutable for one another, and consumers do not explicitly choose between them. This assumption has been found empirically to be true for games on some platforms, but not all (see Nair (2007) and Derdenger (2010). I provide supporting evidence for this assumption in the context of popular XBOX 360 video games, the ones used in estimation, in Appendix A. Third, this setup implies that used and new games are perfect substitutes for one another. Since used games provide the same service as new games, it seems quite reasonable that this assumption would nearly hold. This is supported by the fact that used games are sold for about the same price as new games - about 10% less than new games in brick and mortar stores, and about 5% less online.\footnote{Used game prices in the data appear to be substantially lower than new game prices. However, this is due to a difference between the prices at online auctions, regardless of whether the game is new or not, and the price at reputable brick and mortar stores. The difference is due to implied costs from buying via an online auction: time costs of waiting for it to be delivered and risk of being scammed or receiving a broken product.}

In the remainder of this subsection, I present the specifics of the demand model for a single game. I start by presenting the flow utilities. Then, I describe the transition processes of the state variables from the perspective of consumers. Next, I introduce the value functions. Finally, I describe the policy functions, which are an input in the estimation procedure. This process is repeated for each game during estimation.

### 3.1.1 Flow Utility

There are four possible actions consumers can take at some point: buying, waiting to buy, keeping, and selling. Note, however, that the choice set, i.e. which of these options are available, depending on ownership status. For example, non-owners do not have the option to sell.

The mean flow utility of buying a game is:

\[
u_{\text{buy}}(\tilde{\delta}_i, \xi, P) = \tilde{\delta}_i + \xi - \alpha P + \varepsilon_i = \bar{u}_{\text{buy}}(\tilde{\delta}_i, \xi, P) + \varepsilon_i
\]  

where \(\tilde{\delta}_i\) is the mean flow utility of the product to individual \(i\) at first use, \(\xi\) is a transient utility shock common across individuals, \(P\) is the price, and \(\varepsilon_i\) is the individual specific shock.
that period. The function \( \bar{u}_{\text{buy}} (\tilde{\delta}_i, \xi, P) \) equals the flow utility of buying minus \( \varepsilon_i \), and will be used subsequently for notational purposes.

The mean flow utility of owning is given by:

\[
u_{\text{own}} (\tilde{\delta}_i, \xi, h) = (\tilde{\delta}_i + \xi) B (h) + \varepsilon_i = \bar{u}_{\text{own}} (\tilde{\delta}_i, \xi, h) + \varepsilon_i \tag{2}\]

where \( B (h) \) is a function that reflects the decrease in value due to length of previous ownership \( h \). I parameterize \( B (h) \) as \( B (h) = \lambda_1 \exp (\lambda_2 h) - (1 - \lambda_1) \), where \( \lambda_1 \geq 0, \lambda_2 \leq 0 \). I assume that \( h \) is capped at 12, i.e. subsequent ownership periods beyond 12 do not change the value of the \( B (h) \) function.

The mean flow utility of the outside good equals:

\[
u_{\text{wait}} = \omega + \varepsilon_{i,0} = \bar{u}_{\text{wait}} + \varepsilon_{i,0} \tag{3}\]

where \( \omega \) is the outside good value and \( \varepsilon_{i,0} \) is the individual specific shock that period to the utility of not owning. It is normalized to a positive value to ensure that all \( \delta \) are positive. As long as this holds, the actual value of \( \omega \) is inconsequential. If and when \( \delta \) were less than zero, the model equations would imply that tiring of the product would increase the valuation for it, which does not make sense.

The mean flow utility of selling is given by:

\[
u_{\text{sell}} (P_{\text{sell}}, \zeta) = \omega + \alpha P_{\text{sell}} + \zeta + \varepsilon_{i,0} = \bar{u}_{\text{sell}} (P_{\text{sell}}, \zeta) + \varepsilon_{i,0} \tag{4}\]

where \( P_{\text{sell}} \) is the price at which owners can resell the product, \( \zeta \) is a transaction cost shock common across individuals, and \( \alpha \) is the same as in the buying equation. The transaction cost shocks can result, for instance, from differences between the quality perceived by non-owners and realized quality of the product that period.

I assume that the \( P_{\text{sell}} \), the amount a consumer can sell a used product for, is a function of \( P \) to be estimated from the data.\(^{18}\) Specifically,

\[
P_{\text{sell}} = f (P) \tag{5}\]

Deviations from this relationship are accounted for by \( \zeta \).

\(^{18}\)The primary avenues for consumers to resell their games were brick and mortar store and online auctions (e.g. eBay). Interviews with managers at brick and mortar stores revealed that the prices paid to resellers were similar online and in store, and were much less than new game prices. However, a subsequent buyer of the used game would typically pay close to the new price in a store, but much less through online auctions. This price difference is due to implied risk costs associated with buying a game online. For example it is not guaranteed to work, or the auction might be a scam. Additionally, there is an implied cost of waiting to receive the game by mail when buying online.
3.1.2 Heterogeneity

Managers have noted the video game market consists of two groups of consumers, "hardcore gamers" and the "mass market." I use latent class approximation to the bimodal distribution of valuations (Kamakura and Russell, 1989). I assume there are two types, where type is denoted by $k$. The low type has intrinsic value of ownership equal to $\delta_k = \delta$, and the high type has intrinsic value equal to $\delta_k = \delta + \beta$. The fraction of high types amongst the population is given by the parameter $\gamma$.

The fraction among non-owners and owners changes endogenously over time, however. In early periods, high type consumers are more likely to purchase, so naturally the fraction of remaining non-owners that are of the low type increases over time.

3.1.3 State and Control Space

While there is only one control variable, ownership, there are several other relevant state variables. They are the price ($P$), previous periods of ownership ($h$), demand shock ($\xi$), transaction cost shock ($\zeta$), and individual specific utility shocks ($\varepsilon_i$ and $\varepsilon_{i,0}$) each period. Ownership status and previous periods of ownership are deterministic. The remaining state variables are stochastic from the perspective of consumers.

Following Nair (2007), I assume that expected changes in prices and mean intrinsic utilities from the consumers’ perspective are random and correlated. Specifically, I assume that the price process is Markovian, and thus is well approximated as:

$$P' = g(P) + \eta'$$

where the $g(P)$ is a function to be estimated from the data, and $\eta$ is the component of the change in price unpredictable to consumers. Also following Nair (2007), I assume that the mean value ($\bar{\delta}$) equals a constant quality amount $\bar{\delta}$ plus a common utility shock $\xi$, i.e.:

$$\delta_i' = \bar{\delta} + \xi'$$

where $\xi$ is the unanticipated component of mean utility each period common across individuals. I assume that $\xi$ does not exhibit autocorrelation, but allow it to be correlated with the price shock. Specifically, I assume $\eta$ and $\xi$ are distributed jointly normal with nonzero correlation ($\rho_{\xi,\eta}$).

Like $\xi$, each of the remaining state variables ($\zeta, \varepsilon_i, \varepsilon_{i,0}$) are assumed to be independently distributed across time, and hence are uncorrelated with all state variables. This implies

\footnote{See Nair (2007).}
that they follow Rust’s (1987) conditional independence assumption. For functional forms, I assume $\zeta$ are distributed normally, and $\varepsilon_i$ and $\varepsilon_{i,0}$ follow the type 1 extreme value distribution with location parameter equal to the negative of Euler’s constant and scale parameter equal to one.

### 3.1.4 Value Functions

The non-substitutability of video games implies that the ownership control variable is binary. Hence, for presentation purposes, the value function can be broken into two value functions conditional on ownership status.

For both value functions, one can yield a simplified Bellman equation on a reduced state space without $\xi$, $\zeta$, $\varepsilon_i$, and $\varepsilon_{i,0}$, by integrating over these states, since they are distributed independently of all state variables and thus do not inform on the probabilities of future states (Rust, 1987). This results in the expected value of the value function before any of these three variables are known. The states $\varepsilon_i$ and $\varepsilon_{i,0}$ can be integrated out analytically, following Rust (1987), however $\zeta$ and $\xi$ must be integrated out numerically.\(^2\)

Following the steps above, the Bellman equation for an individual of type $k$, conditional on owning, can written as in equation 8 below.

$$W_O(S) = \int \ln \left\{ \exp \left( \bar{u}_{own}(S, \xi) + \varphi E [W_O(S')] \right) + \exp \left( \bar{u}_{sell}(S, \zeta) + \varphi \frac{\omega}{1 - \varphi} \right) \right\} df(\xi, \zeta)$$

(8)

where the state variables $S = \{\delta_k, P, h\}$, $\varphi$ is the discount factor, and $E[]$ denotes the expectation taken over future price, $P'$.

Likewise, the value function, conditional on non-ownership, $W_{NO}$, can be written as:

$$W_{NO}(S) = \int \ln \left\{ \exp \left( \bar{u}_{buy}(S, \xi) + \varphi E [W_O(S')] \right) + \exp \left( \bar{u}_{wait} + \varphi E [W_{NO}(S')] \right) \right\} df(\xi)$$

(9)

### 3.1.5 Policy Functions

An owner will sell the product if the expected discounted utility of selling exceeds the expected discounted of utility of keeping. Specifically, the optimal policy is selling if and only if:

$$\bar{u}_{sell}(S, \zeta) + \varphi \frac{\omega}{1 - \varphi} + \varepsilon_{i,0} > \bar{u}_{own}(S) + \varphi E [W_O(S')] + \varepsilon_i$$

(10)

\(^2\)When $\varepsilon_1$ and $\varepsilon_2$ follow the type 1 extreme value distribution with location parameter equal to the negative of Euler’s constant, and scale parameter equal to one: $E[\max(A + \varepsilon_1, B + \varepsilon_2)] = \ln(e^A + e^B)$. See Rust (1987), equation 4.12.
Assuming the error terms $\varepsilon_i$ and $\varepsilon_{i,t}$ follow the type 1 extreme value distribution, the probability that non-owner $i$ of type $k$ with $h$ previous ownership sells can be written analytically as:

$$s_{k,\text{sell}}(S, \xi) = \frac{\exp(u_{\text{sell}}(S, \xi) + \varphi \frac{W_{\text{O}}(S)}{W_{\text{O}'}})}{\exp(u_{\text{sell}}(S, \xi) + \varphi W_{\text{O}}(S) + \varphi E[W_{\text{O}}(S)']) + \exp(u_{\text{own}}(S) + \varphi E[W_{\text{O}}(S)'])}$$

(11)

Following analogous steps, the probability of non-owner $i$ of type $k$ buying can be written as:

$$s_{k,\text{buy}}(S, \xi) = \frac{\exp(u_{\text{buy}}(S, \xi) + \varphi E[W_{\text{O}}(S)'])}{\exp(u_{\text{buy}}(S) + \varphi E[W_{\text{O}}(S)']) + \exp(u_{\text{wait}} + \varphi E[W_{\text{NO}}(S)'])}$$

(12)

### 3.2 Supply

Rather than fully modeling the supply side, I use a simplified supply side to impose an optimal price level constraint in estimation. Including a full supply side would introduce a couple of problems in estimation: it would require strong assumptions on firm decision-making processes such as the extent to which they can commit to maintaining prices, and would be substantially more expensive computationally, making it infeasible.

The specific constraint used is the derivative of discounted profits with respect to the first period price must equal zero, assuming that subsequent prices follow the estimated price path function. This constraint implies that the firm cannot raise profits by changing the initial price, holding fixed the estimated decline in prices over time, given by the $g()$ function from equation 6.

Specifically:

$$P_{t}^{\text{alt}} = \begin{cases} P_{1} + c & \text{if } t = r \\ g(P_{t-1}^{\text{alt}}) + \eta_{t} & \text{if } t > r \end{cases}$$

(13)

where $r$ is the release date of the product, $t$ denotes time, and $\eta_{t}$ is the error from the regression from equation 6.

The firm’s discounted profit equals:

$$\pi(P^{\text{alt}}) = \sum_{t=1}^{\infty} (P_{t}^{\text{alt}} - MC) * Q_{\text{new}}(S(P_{t}^{\text{alt}}), \xi)$$

(14)

where $MC$ is the marginal cost to the software producer, and $Q_{\text{new}}(S(P_{t}^{\text{alt}}), \xi)$ is the quantity of new goods sold. Following the literature, I assume that the marginal cost equals
$11.50, i.e. $10 in royalty fees plus $1.50 in production costs.\textsuperscript{21} \( Q_{\text{new}} (S \left( P_{t}^{\text{alt}} \right); \xi) \) equals the total quantity bought, \( Q_{\text{bought}} (S \left( P_{t}^{\text{alt}} \right); \xi) \), minus the quantity of sales which are displaced by used good sales, \( Q_{\text{used}} (P_{t}^{\text{alt}}) \). These quantities equal:

\[
Q_{\text{bought}} (S, \xi) = \sum_{k} M_{k} \ast s_{k,\text{buy}} (S, \xi) \tag{15}
\]

\[
Q_{\text{used}} (S, \xi) = \sum_{k,h} R_{k,h} \ast s_{k,\text{sell}} (S, \zeta) \tag{16}
\]

where \( M_{k} \) is the mass of consumers of type \( k \), \( R_{k,h} \) is the mass of owners of type \( k \) with \( h \) previous periods of ownership, and \( s_{k,\text{buy}} (S, \xi) \) and \( s_{k,\text{sell}} (S, \zeta) \) are the model’s predicted share of a type buying and selling (from equations 11 and 12).

With these assumptions, I can implement a price level constraint without needing the full dynamic equilibrium. Instead, I require the starting price on average be profit maximizing given that prices evolve according to the observed price submartingale estimated from the data.

### 4 Estimation

The model is estimated by maximum likelihood, subject to the aforementioned constraint. Specifically, the likelihood function equals:

\[
L (data; parameters) = \prod_{j,t} L (P_{j}, Q_{j}^{\text{new}}, Q_{j}^{\text{used}}; \lambda, \alpha, \beta, \gamma, \sigma_{\xi}, \sigma_{\eta}, \sigma_{\zeta}, \rho_{\xi,\eta}, \varphi) \tag{17}
\]

where \( j \) denotes product, \( \lambda \) determines the rate of boredom, \( \alpha \) is the price sensitivity, \( \beta \) and \( \gamma \) determine the distribution of types, \( \sigma_{\xi}, \sigma_{\eta}, \) and \( \sigma_{\zeta} \) are the standard deviations of demand, price, and transaction cost shocks, \( \xi, \eta \) and \( \zeta \), \( \rho_{\xi,\eta} \) is the correlation between \( \xi \) and \( \eta \), and \( \varphi \) is the discount factor. Prior literature has noted problems in estimating the discount factor in dynamic models. Following Nair (2007), I assume the value of the month-to-month discount factor equals 0.975.

After a change of variables transformation, the likelihood can be written in terms of the price, demand, and transaction cost shocks, as:

\[
L (\eta, \xi, \zeta; \theta) = \prod_{j,t} f (\eta_{j}; \xi_{j}; \theta) f (\zeta_{j}; \theta) ||J|| \tag{18}
\]

\textsuperscript{21}See Nair (2007).
where $||J||$ is the Jacobian determinant. The derivation of the Jacobian is shown in Appendix B. The price shocks $\eta$ are estimated a priori from the data, according to equation 6. The demand and transaction cost shocks ($\xi$ and $\zeta$) are recovered within each iteration, by the method described in the next subsection.

The likelihood is maximized subject to the supply-side constraints:

$$\frac{d\pi}{dP_1} = 0$$  \hspace{1cm} (19)

where $\pi$ is calculated according to equation 14, and a change in the first period price implies a change in prices in all periods, according to equation 13. In practice, restrict the profits to profits made in the first year following a game’s release, during which I observe $\eta$ for all games, which is necessary to calculate prices. This restriction is not meaningful - since most new sales are up front and prices drop over time, nearly all profits from a game are made in the first year after it is released.

### 4.1 Recovering Error Terms

To compute the values of the demand and transaction cost shocks, $\xi$ and $\zeta$, for a single product and period, I follow the method in Gowrisankaran and Rysman (2010), Nair (2007), and Schiraldi (2010). In each iteration in the maximization procedure, the value functions are computed first. Next, the demand shocks $\xi$ are computed sequentially for each period and product, by finding the value that equalizes the observed share buying and predicted share buying. Finally, the transaction cost shocks $\zeta$ are computed each period by finding the value equalizing the predicted and observe share selling. Details are provided below.

The values of $\xi$ are found sequentially using Berry, Levinsohn, and Pakes’ (1995) contraction mapping to find the values $\xi$ which equalize observed and predicted aggregate share buying.\(^{22}\) The formula for the model’s predicted market share buying is:

$$s_{\text{buy}} (S, \xi) = \frac{\sum_k M_k * s_{k, \text{buy}} (S, \xi)}{\sum_l M_l}$$  \hspace{1cm} (20)

where $M_k$ equals the mass of non-owners of type $k$ in the market at the beginning of the period.

The mass of consumers in the first period equals the installed base of potential consumers in that period. In subsequent periods, it is updated to reflect buyers, who have exited the

\(^{22}\)When $\xi$ follows rust’s *1987) conditional independence assumption, the contraction mapping from Berry et. al. (1997) still holds.
market, and incoming potential consumers that were not in the market for the game in the
previous period, for example because they had not yet joined the platform (i.e. bought the
console). I estimate the initial market size and the incoming potential consumers, assuming
that the number of entering consumers for a game is the same over time and equals the
number of buyers each period after the price has plateaued to $6. Details and justification
for this approach are provided in appendix C. The fraction of entering consumers of a given
type (and in the first period the installed base) then equals the total amount multiplied by
the fraction of consumers that are of that type ($\gamma$). The formula for updating the masses
of non-owners in each period after the game is released is given below:

$$M'_k = M_k * (1 - s_{k,\text{buy}}(S)) + M^\text{new}_k$$

(21)

where $M^\text{new}_k$ is the incoming (new) group of potential consumers of type $k$ entering each
period.

The transaction cost shocks ($\zeta$) can be found through a similar method. In each period
beyond the first, $\zeta$ is found by equalizing the model’s predicted and actual share of owners
selling, again using the contraction mapping in Berry, Levinsohn, and Pakes (1995). The
formula for the predicted share selling is:

$$\bar{s}_{\text{sell}}(S, \zeta) = \frac{\sum_{k,h} R_{k,h} * s_{k,\text{sell}}(S, \zeta)}{\sum_{k,h} R_{k,h}}$$

(22)

where $R_{k,h}$ is the mass of owners of type $k$ with $h$ previous ownership periods at the beginning
of the period.

The mass of owners of each type and previous ownership length, $R_{k,h}$, evolves similarly
to masses of non-owners. Before the product is introduced, there are no owners. After the
good is released, the masses of owners are updated each period by:

$$R'_{k,h} = \begin{cases} M_k * s_{k,\text{buy}}(S) & \text{for } h = 1 \\ R_{k,h-1} * (1 - s_{k,\text{sell}}(S, \zeta)) & \text{for } h > 1 \end{cases}$$

(23)

This equation says that the number of owners of discrete type $k$ with one period of previous
ownership simply equals the mass of buyers of type $k$ in the previous period. The mass of
owners of type $k$ with $h > 1$ previous periods of ownership equals the mass of individuals of
type $k$, who in the previous period had $h - 1$ previous ownership periods and decided not to
sell.
4.2 Controlling for Endogeneity

The now standard method of controlling for endogeneity in discrete choice models of demand, which involves interacting the mean error terms, $\xi$ and $\zeta$, with a set of instruments (Berry, Levinsohn, and Pakes, 1995), does not work in this context because it requires having at least as many instruments as parameters. The only variables varying across time in this dataset are prices, quantities (new and used), and number and age of other goods. Typical instruments constructed from these variables are not strong in this context. Bresnahan-style instruments (Bresnahan 1981, 1987), which assume competitive conditions influence the price-cost markup, cannot be used since games have been shown empirically not to be substitutable for each other. Hausman-style instruments (Hausman, 1996, Hausman and McFadden, 1984), which rely on the assumption that marginal cost shocks are correlated across markets, are ruled out, since the marginal production costs of video games, and more generally information goods, are close to zero, and the royalty fees are assumed to have negligible variation.

To control for endogeneity, I use the alternative method from Villas-Boas and Winer (1999), Rossi et al. (2005), Nair (2007) and Jiang et al. (2009). The method involves first estimating a reduced form regression of price on an instrument for price, typically lagged price, and recording the residuals. Note that the residuals encompass the endogenous component of price. Then, with these residuals known, the dependence of price changes on demand changes can be explicitly accounted for by allowing the demand shocks and the price residuals from this IV regression to be correlated, where the exact extent of the correlation is estimated within the model.

4.3 Identification

The heterogeneity in intrinsic valuations ($\beta, \gamma$) is identified by the average trends in prices and in the share of non-owners buying. To explain how, I borrow an argument from Nair (2007). Both the price and implicit rental cost, i.e. the price at time of purchase minus the amount received when selling the product, decline on average over time. However, the quality $\delta$ on average stays the same. Hence, the expected gain from buying typically increases over time. If valuations were homogenous, the share of non-owners buying should increase over time as well. If valuations are heterogeneous, higher valuation individuals buy with higher probability, leaving in later periods a greater share of low valuation types, who are less likely to buy than high types. As a result, the share buying can decline over time despite the fact that the appeal of buying to any given non-owner increases over time on average. The exact trends in share buying reflects the extent of heterogeneity.
There are two sources of identification for the price sensitivity ($\alpha$). The first source is cross-sectional variation in prices and share of non-owners buying, along with the assumption that heterogeneity is the same across products. The latter assumption allows the model to pin down responses in the share buying due to price shocks separately from that due to heterogeneity. The second source of identification is the constraint that profit maximizing price level equals the observed price level. This constraint does not by itself identify $\alpha$, since an infinite number of combinations of $\alpha$ and the mean value of use $\delta$ yield the same profit maximizing prices, but the constraint does impose a one-to-one relationship between $\alpha$ and $\delta$, providing further information on the value of $\alpha$.$^{23}$

The coefficient of lost interest ($\lambda$) generates the time pattern of used sales over time, and is pinned down by within-game variation in used sales and the distribution of length of ownership, which reflects previous buying behavior. Higher boredom implies consumers are more likely to sell the product soon after purchase, which translates into a more active resale market.

The coefficient of lost interest and heterogeneity parameters are separately identified. While an infinite number of sets of $\lambda$ and initial valuations can result in an individual wanting to sell the game after $h$ periods but not after $h-1$ periods, given price, not all the sets can explain the individual’s willingness to buy initially, because the individual must yield enough usage utility (in expectation) to justify paying the price to purchase the product. This implies that her first $h$ uses must in expectation be valued at least as high as the difference in the buying and expected selling prices in the period that she buys, but less than the difference in buying and expected selling prices in earlier periods when that difference was larger. A series of inequalities like these allow the coefficient of lost interest to be separately identified from the heterogeneity parameters.

Cross-sectional variation in used sales and prices allows separate identification of the correlation parameter $\rho_{\xi,\eta}$ and the price sensitivity $\alpha$. Both the equations for the probability of buying and for the probability of selling depend on $\alpha \ast \eta$ and $\xi$, where $\eta$ is known. In either equation alone, $\alpha$ and the correlation between $\eta$ and $\xi$ are not separately identified. But, because $\xi$ is interacted with $B(h)$ only in the equation for the probability of selling, the marginal effects of $\xi$ differs across these equations. Hence, while there are an infinite combination of combinations of $\rho_{\xi,\eta}$ and $\alpha$ that satisfy one of these equations, the same cannot be said for both equations simultaneously. Rather, there should be a fixed point satisfying both equations simultaneously. This argument is analogous to solving for two

$^{23}$In the static case with homogeneous buyers, one can show that the derivative of profits with respect to price can equal zero at an observed price for an infinite number of combinations of the price sensitivity and mean utility of use, implying the profit-maximizing condition alone is insufficient for identification.
unknowns, using two equations. If the two equations are linearly independent, then the second equation provides additional information, and both parameters can be separately determined.

4.4 Counterfactual Computation

To find the price paths arising from a Markov Perfect rational expectations equilibrium game between firms and consumers in the counterfactual legal environment where resale markets are shut down, I use a policy iteration procedure similar to Nair’s (2007).\textsuperscript{24} The resulting policy functions for each player account for their own impact on the evolution of states, and are optimal given the calculated policy functions of the other players in the game.

The consumers’ policy functions mostly follows from the demand estimation section. The value functions for not owning and the corresponding policy functions \((s_{k,\text{buy}}(S))\) are calculated via equations 9 and 12. When resale is not allowed consumers choose each period between keeping the product and disposing of it for no compensation or cost. The only changing state variable is \(h\), which is deterministic. In this case, the value function of owning follows from simple backwards induction from the expected discounted value at the highest value of \(h\) allowed, \(H\). The value function of owning at \(H\) is found by iterating on the Bellman equation for the steady state at \(h = H\).

There is one large difference between the specification of the consumer value and policy functions in demand estimation and in the counterfactual model. In demand estimation, because the observed price path was an equilibrium outcome under existing laws, the current value of price characterized consumer expectations of future prices, and was therefore included as a state variable. In a counterfactual equilibrium game, the price state variable needs to be replaced by several state variables which imply price through the firm’s policy function \((P(S))\). These state variables are the masses of non-owners of each type relative to the number of entering potential consumers, and they evolve according to equation 21.

The profit-maximizing firm policy function follows from the static profit function and the evolution of states. The static profit function is:

\[
\pi(S, P) = (P - MC) \times Q(S, P)
\]  

(24)

where \(Q(S, P)\), the quantity purchased, is given by equation 15. The firm’s value function equals:

\textsuperscript{24}Nair notes that the equilibrium is not guaranteed to be unique. However, he found that multiple starting values converged to the same equilibrium. Though, this does not rule out a boundary solution.
\[ V_{\text{Firm}}(S) = \max_P \{ \pi(S, P) + \varphi V_{\text{Firm}}(S'|S, P) \} \quad (25) \]

where the set of state variables, \( S \), are the state variables characterizing the demand conditions - the masses of non-owners of each specific type. These variables according to equation 21. The firm’s policy function is simply the profit maximizing price at each state:

\[ P(S) = \arg \max_P \{ \pi(S, P) + \varphi V_{\text{Firm}}(S'|S, P) \} \quad (26) \]

The numerical procedure proceeds by four steps. The first step is simply to guess at both the consumers’ policy functions, \( s^{0th}_{k,\text{buy}}(S) \) and their expectations for the evolution of the state variables, \( M'(s^{0th}_{k,\text{buy}}(S)) \). The "0th" denotes the initial guess. In the second step, the \( n^{th} \) guess, where \( n \) starts at 1, at the the firm’s value and policy functions, \( V^{nth}_{\text{Firm}}(S) \) and \( P^{nth}(S) \), are calculated via value function iteration, conditioning on the most recent guess of the consumers’ policy functions, \( s^{(n-1)th}_{k,\text{buy}}(S) \). The third step iterates on two substeps. The first substep is calculating the expected next period states as a function of current states \( M'(s_{k,\text{buy}}(S)) \), and the consumer’s policy functions, \( s_{k,\text{buy}}(S) \). Then in the next substep the consumer policy functions, \( s_{k,\text{buy}}(S) \), are recomputed given these updated expectations. These two substeps are repeated until the total absolute difference between the consumer’s policy functions’ between iterations on the substeps is sufficiently small. This concludes the third step, yielding the next guess of the consumer’s policy function, \( s^{nth}_{k,\text{buy}}(S) \). The fourth step iterates on steps two and three until the total absolute difference in the firm’s policy function between iterations is smaller than some arbitrary value, at which time the procedure stops.

5 Results

The first steps are to estimate some reduced form functions that will be fed into the model. Specifically, we need exact functions for equations 5 and 6.

An estimate of Equation 5, which relates the price at which a consumer can buy a game to the price they are paid to sell it, might seem to be complicated by the fact that consumers have two choices of where to resell games, at online auctions or at brick and mortar stores, whereas the data only includes prices from online auctions. However, Interviews with store managers confirmed that the online price for used games at online auction sites, comprising the data on \( P_{\text{sell}} \), is similar to the price paid by brick and mortar stores to consumers consumers reselling games. Hence, it can be used to represent the market price at which
Equation 5 is estimated by a regression of \( P_{\text{sell}} \) on \( P \). The regression, which yields an R-square of 0.78, implies the following relationship between \( P_{\text{sell}} \) and \( P \):

\[
P_{\text{sell}} = -4.217 + 0.677P
\]  

(27)

The price evolution process in equation 6 is estimated, from the perspective of consumers. Consumers can base their expectations of future prices on readily observable information such as current and past prices, and game characteristics like critic review scores and game genre. To test which observables impact future prices, I estimate an autoregression of price on lagged prices and game characteristics:

\[
P_{j,t} = \gamma_1 + \gamma_2 P_{j,t-1} + \gamma_3 P_{j,t-2} + \ldots + \gamma_m P_{j,t-m} + \text{game_characteristics}_j + \varepsilon_{j,t}
\]  

(28)

The results in Table 3 shows that the previous period price is a strong predictor of current period price. The R-squared value shows lagged price accounts for over 90 percent of the variation in prices. However, the twice lagged price is not significant when added to the regression. Additionally, there is no evidence of autoregressive disturbances. The correlation between residuals and lagged residuals from the preferred regression (number 4) is negative, near zero and hence not economically meaningful, and insignificant.

Table 3 does show that the critic score quintile is a significant predictor of the price decline. In the estimation model, I include only games of the highest quintile of critic reviews scores.

The estimated lagged price regression for the highest quintile of games equals, used as equation 6 in the model, equals:

\[
P' = \kappa P + \eta'
\]  

(29)

where \( \eta' \) is the portion of next period price which is not anticipated by consumers. The parameter \( \kappa \) equals 0.96, and and \( \eta \) is normally distributed with \( \sigma (\eta) \approx 4.93 \).

With equations 5 and 6 specified, the model is estimated. The sample of games in estimation is restricted to games in the highest critic quintile that were released in the first two years following the platform’s release, for which a full 12 months of data for each game

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25 This differs from the true cost of buying a used game. Used games sold by brick and mortar stores to consumers cost nearly the same amount as new games, and online auction prices do not reflect additional costs borne by the buyers, such as shipping costs, time costs of waiting, and implied risk costs of buying from an unknown seller.
are available. The values of parameters, and their standard errors, are reported in Table 4.

The rate at which consumers tire of products and the heterogeneity in initial valuations, the two factors expected to have the biggest impact on the effect of resale markets, are depicted graphically in Figure 3. Before owning the product, the "hardcore gamers" value one-period use of the game about 8 utils, or about $16, more than do the "mass market" types. Both types lower value of one-period use quickly with ownership length. The high types, for example, value one period of use about 30 utils, or about $60 more than they value the outside good before having used the product, but after about four months of use, the outside good on average provides greater one-period value to them than the game does. The fast rate at which consumers lose interest suggests that the impact of resale markets on firm profits may be substantial.

The second and fourth columns of Table 5 shows the demand elasticity estimates at different ages of game. The second columns shows the static (one period) elasticities of demand. The rightmost column shows the dynamic elasticity of demand. Specifically, it shows the percent change in the quantities for the three months following a percent change in price, assuming that the prices and expectations of prices adjust to a one period price change according to equation 6. Notice first that the static elasticity of demand remains roughly the same over time. Their average magnitude, about −2, is similar to previous elasticity estimates for console video games in Nair (2007). The dynamic elasticity for total goods are uniformly lower than their static counterparts. This was expected. Keane (1997) points out price elasticities for storable goods should include demand displaced from future periods. However, the magnitude of the elasticities does not seem to depend strongly on dynamics.

The difference in the elasticities of demand for goods and the elasticity of demand for new goods, where new good demand simply equals total demand minus used good supply, is indicative of the effect of used sales. Note that while there is no clear trend in the elasticity of demand for goods, the elasticity of demand for new goods starts at the same level as the demand for goods, but increases nearly threefold over time. This is true for both the static and dynamic elasticity estimates. This pattern reflects the fact that when used sales are allowed, a one unit increase in price has two effects. It has the normal impact of reducing the quantity demanded. In this case it also makes selling more attractive to owners and hence increases used good sales, displacing more new sales. This suggests that used good sales put a strong downward pressure on the price charged for new goods.

The estimated values of the standard deviations of ξ and ζ show that the change demand tends to be much smaller in magnitude than the transient transaction cost shock. The standard deviation of the demand shock, ξ, equals about 1.7. Since δ on average is about
22 utils higher than the outside good, this represents about 8% of the typical initial static one period valuation for the good. The standard deviation of the transaction cost shock $\zeta$, is higher at 9.1. This is equivalently 41% of the typical difference between $\delta$ and the outside good value $\omega$. The magnitude of the standard deviation of $\zeta$ is partially explained by random deviations from the relationship between the buying and selling prices in equation 27, but is also in part due to restrictive functional form assumptions.

The model fit can be tested using the values of the demand and transaction cost error terms in the model, which are assumed to be mean zero each period. Specifically, I can test the functional form assumptions by looking for systematic deviations over time. Figures 4A and 4B show plots of the demand shocks and transaction cost shocks, respectively, over game age. There does appear to be some bias in these shocks across time. Both decline over the games age, meaning that the shocks are simultaneously making buying and selling less attractive on average as time progresses than predicted by the model. A more flexible functional form for heterogeneity is likely to provide a better fit.

The estimation results show that the endogeneity is meaningful in the model. The estimated correlation between the price and demand shocks, $\xi$ and $\eta$, is 0.5, implying a substantial portion of price shocks are attributable to demand shocks.

### 5.1 Counterfactual Results

The summary statistics from the simulations, shown in Table 6, show a rather striking result. Firm profits in the first year following a games release are over 100% higher when resale is prohibited compared to when it is allowed.

This finding contrasts with the existing theory, which finds that resale should not lower firm profits. However, the existing literature does not allow consumers to tire of goods with use.

In the model for goods consumers tire of, however, I find that used sales have an additional impact which causes them to reduce firm profits. Resale markets in this model cause price declines over time, because residual demand is fulfilled by secondhand goods. This in turn introduces an incentive compatibility constraint; consumers will not pay as much to buy the product immediately if they know the price will fall quickly. Figure 5 shows the impact of resale markets on optimal prices. When resale is prohibited, the firm maintains a high price across time. As a result, consumers do not have much incentive to wait. However, when resale is allowed, price falls sharply over time, even though in this case the firm sells almost all of its goods in the first period. Consumers in the model anticipate the falling

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26 Discount factors less than one and used sales transaction costs can lower profits under the existing theory. They partially drive the empirical results.
price, and fewer are willing to pay the high price initially, despite the fact that the good is
worth more to them when resale is allowed, since they then have the additional option to
resell the good.

Table 6 also shows that the firm sells substantially more goods when resale markets are
prohibited, about 3.5 times as much in the first year. When resale markets do not exist, each
buyer purchases their own copy from the firm. By contrast, with allowed resale markets,
individuals share goods across time through used-market transactions. Additionally, since
prices remain roughly flat when resale is prohibited, there is less incentive to delay purchase.

A related question is what impact resale markets have on consumers, after accounting for
the firm’s response to them. I calculate the exact net welfare gain from resale markets using
Small and Rosen’s (1981) formula for Hick’s (1939) equivalent variation. The net welfare
gain to an individual of type \( k \), in dollars, equals:

\[
EV_k = \frac{W_{NO,YR}(k,1) - W_{NO, NR}(k,1)}{\alpha}
\]

(30)

where \( \alpha \) is the price sensitivity, and \( W_{NO,YR}(k,1) \) and \( W_{NO, NR}(k,1) \) are the value functions
at game release, conditional on not owning the good, when resale is and is not allowed,
respectively.\(^{27}\) I find that resale markets raise consumer welfare by $20.84 for each low-type
individual, and by $22.37 per high-type individual, for an aggregate total of approximately
$50.3 million, based on the average market size of 2.3 million. Thus, the profit gain from
shutting down resale nearly offsets the loss to consumers - welfare increases by a measly
$0.3 for the average game when resale is shut down. The reason the gain is positive is that
fewer consumers delay purchase when resale is allowed and hence on average do not discount
utility from its use as much.\(^{28}\)

6 Discussion and Conclusion

Contrary to traditional theory, which holds that resale markets should not reduce profits of
producers of perfectly durable goods, I found evidence that in markets that have the feature
that consumers tire of goods, allowing resale does significantly reduce firm profits. Using
data from the video game market, I found that consumers in fact tire of video games very
quickly, and as a result market prices decline quickly as used goods are resold to consumers

\(^{27}\) Value function in the case of prohibited resale is calculated using the policy iteration method for the
average value of \( \delta \). The corresponding value function for when resale was allowed was calculated additionally
assuming the average prices each period followed the averages across the games in estimation.

\(^{28}\) The welfare calculation does not include a third group, resale market makers, whose profit would increase
welfare when resale is allowed. Their profits cannot be estimated because their cost functions are not known.

23
with lower valuations for the product. I found that prohibiting resale raises firm profits substantially, because it allows firms to maintain high prices.

A related question, not directly investigated in my paper, is whether resale will change the size of investments in video game development. I argue that it is unclear whether these investments will change. One the one hand, if firms are able to capture a greater share of the area under the demand curve, then they have more incentive to invest in products. One the other hand, they are limited greatly by the availability of technology, which is likely exogenous to video game development, because computing power and software development tools evolve to fit the needs of many different industries, of which video games are a small part. If video game developers are already utilizing the most modern development tools, then resale markets should not impact the quality of aspects like graphics or special effects. However, if resale is prohibited, it is also possible that developers will invest more in the game’s storyline. So I cannot rule out the possibility that the existence of resale markets alters optimal investments in game development.

A third question is whether the ability to shut down resale markets by distributing products digitally will lead to firms utilizing inefficient distribution channels. For example, book publishers may only distribute digital versions of their products, forcing individuals to buy a Kindle or similar device in order to read books, even if the large marginal production costs of Kindles makes such distribution inefficient. I leave this issue for future work.

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Appendices

A  Evidence that Games are Not Substitutes

Earlier papers focusing on video games have found that whether or not games are substitutes for one another depends on the platform/generation in question. Nair (2007) argued that because there are a large number of games, and because “each game is fairly unique, having its own distinct features, characters and idiosyncrasies,” that they are likely not substitutes for one another. He then showed empirically that Playstation 2 games do not appear to be substitutes for one another. Specifically, he demonstrated that (1) that there are no statistically significant cross-price effects within genre, (2) neither sales nor prices are significantly impacted by hit game releases in the same genre, and (3) that concentration in a genre does not significantly impact the rate at which prices decline. However, Derdenger (2010) found that games were statistical substitutes when also looking at games on the two other 6th generation consoles (Gamecube and XBOX), by repeating Nair’s first test of whether there are cross-price effects within genre. Hence, it seems that whether or not games are substitutable on a newer generation of consoles is an empirical question.

To test whether XBOX 360 video games are substitutes in the context in this paper, I employ a static nested logit model analogous to the ones in Nair (2007) and Derdenger (2010) but use XBOX 360 vide game data. The nested logit, with genres determining nests, allows one to test for whether games are cross price substitutes. The specification set forth in Einav (2007) and Nair (2007) (and used in Derdenger (2010)) controls for firms strategically releasing games to avoid cannibalization from other games by including game fixed effects and time since release fixed effects. The exact specification, is:

\[
\ln \left( \frac{s_{jt}}{s_{0t}} \right) = \alpha_j + \omega_t + \lambda (t - r_j) + \beta P_{jt} + \sigma \ln \left( s_{jt|g} \right) + \varphi_{jt} \tag{31}
\]

Where \( s_{jt} \) and \( s_{0t} \) are the shares of game \( j \) and the outside good in period \( t \), respectively, \( \alpha_j \) and \( \omega_t \) are game and month fixed effects, \( r_j \) is the release date of game \( j \), \( P_{jt} \) is the price, \( s_{jt|g} \) is the game \( j \)'s share of genre \( g \) sales, and \( \varphi_{jt} \) is an error term. Following earlier papers (Nair, 2007; Derdenger, 2010), I set the total market size for all games together to the cumulative installed base of XBOX 360 console owners.

---

\(^{29}\)This specification tests for the extent to which games in the same genre are more substitutable for each other than games across genres. If games across genres are not substitutes for one another, this is analogous to a test of whether games are substitutes for one another. Games across genres are much less likely to be substitutable, since the gameplay is by far more different. If games are somewhat substitutable, this specification tests whether games within a genre are more substitutable than games across genres.
The value of the parameter $\sigma$ determines the extent to which games are substitutes for one another. A value close to zero denotes that the nests are largely irrelevant and hence games are not substitutes for one another. Higher positive values denote that games are substitutes for one another.

A remaining concern is that two right-hand side variables in equation 31 above, price ($P_{jt}$) and the within genre share of sales ($s_{jt\mid g}$), are likely endogenous. To address this concern, I instrument for them using the lagged price and the number of games in the genre.

The results are shown in Table 7. The sample is restricted sample used in estimation. The first three columns in table 7 employ OLS and varying degrees of polynomials for time since release. The second three employ 2SLS. Note that once the instruments are included, the estimated values of $\sigma$ are negative and insignificantly different from zero, strongly suggesting that games are not substitutable for one another.

\section{B Jacobian}

Note, the quantity predicted to be bought, $Q_{\text{bought}}^{\text{pred}}$, equals:

$$Q_{\text{bought}}^{\text{pred}}(\delta, \xi, P, M) = \sum_k M_{k,t} \Pr(\text{buy}|\delta_k, \xi, P)$$

(32)

Similarly, the quantity predicted to be resold in a period, $Q_{\text{resold}}^{\text{pred}}$ equals:

$$Q_{\text{resold}}^{\text{pred}}(\delta, \xi, P, \zeta, R) = \sum_{k,h} R_{k,h,t} \Pr(\text{sell}|\delta_k, \xi, P, h, \zeta)$$

(33)

From these equations, and the pricing equation, the shocks ($\xi, \eta, \text{and } \zeta$) can be found. $\xi_t$ is found by solving:

$$Q_{\text{bought}}^{\text{pred}}(\delta, \xi, P, M) - Q_{\text{bought}}^{\text{actual}} = 0$$

(34)

and given that $\delta' = \delta + \xi'$,

$$\xi = Q_{\text{bought}}^{-1}(\delta, P, M, Q_{\text{bought}}^{\text{actual}})$$

(35)

$\eta$ is found by:

$$\eta_t = P_t - \kappa P_{t-1}$$

(36)

and $\zeta_t$ is found by solving:
\[ Q_{\text{resold}}^{\text{pred}}(\delta, \xi, P, \zeta, R) - Q_{\text{resold}}^{\text{actual}} = 0 \] (37)

\[ \Rightarrow \zeta = Q_{\text{resold}}^{-1}(\delta, \xi, P, R, Q_{\text{resold}}^{\text{actual}}) \] (38)

The Jacobian determinant thus equals (since \( \delta_t \) is a function of \( \xi_t \), which, by the above functions, is a function of \( Q_{\text{bought}}^{\text{actual}} \)):

\[
\begin{vmatrix}
\frac{\partial \xi}{\partial Q_{\text{bought}}} & \frac{\partial \xi}{\partial P} & \frac{\partial \xi}{\partial Q_{\text{resold}}} & \frac{\partial \xi}{\partial \eta} & \frac{\partial \xi}{\partial \zeta} \\
\frac{\partial \eta}{\partial Q_{\text{bought}}} & \frac{\partial \eta}{\partial P} & \frac{\partial \eta}{\partial Q_{\text{resold}}} & \frac{\partial \eta}{\partial \xi} & \frac{\partial \eta}{\partial \zeta} \\
\frac{\partial \zeta}{\partial Q_{\text{bought}}} & \frac{\partial \zeta}{\partial P} & \frac{\partial \zeta}{\partial Q_{\text{resold}}} & \frac{\partial \zeta}{\partial \xi} & \frac{\partial \zeta}{\partial \eta} \\
\end{vmatrix} = \begin{vmatrix}
\frac{\partial \xi}{\partial Q_{\text{bought}}} & \frac{\partial \xi}{\partial P} & 0 \\
0 & 1 & 0 \\
0 & \frac{\partial \zeta}{\partial P} & \frac{\partial \zeta}{\partial Q_{\text{resold}}} \\
\end{vmatrix} = \left| \frac{\partial \xi}{\partial Q_{\text{bought}}} \right| \cdot \left| \frac{\partial \zeta}{\partial Q_{\text{resold}}} \right| \] (39)

**B.1 Computing** \( \frac{\partial \xi_t}{\partial \eta_{t,\text{resold}}} \)

We know that \( \sum_{k,h} R_{k,h} s_{\text{sell}}^k(S, \zeta) - Q_{\text{resold}}^{\text{actual}} = 0 \). By the implicit function theorem, we have:

\[
\frac{\partial \zeta}{\partial Q_{\text{resold}}} = -\frac{-1}{\frac{\partial}{\partial \zeta} \left( \sum_{k,h} R_{k,h} * s_{\text{sell}}^k(S, \zeta) \right)} \] (40)

Note

\[
\frac{d}{dx} \frac{e^{A+x}}{e^B + e^{A+x}} = e^{B} \frac{e^{A+x}}{(e^{B} + e^{A+x})^2} = \frac{e^{B}}{(e^{A+x} + e^B)} \] (41)

Hence,

\[
\frac{\partial}{\partial \zeta} s_{\text{sell}}^k(S, \zeta) = \left( 1 - s_{\text{sell}}^k(S, \zeta) \right) * s_{\text{sell}}^k(S, \zeta) \] (42)

and we can rewrite:

\[
\frac{\partial \zeta}{\partial Q_{\text{resold}}} = -\sum_{k,h} R_{k,h} \left( 1 - s_{\text{sell}}^k(S, \zeta) \right) * s_{\text{sell}}^k(S, \zeta) \] (43)

**B.2 Computing** \( \frac{\partial \xi_t}{\partial \eta_{t,\text{bought}}} \)

We know that: \( \sum_k M_{k,t} s_{\text{buy}}^k(S, \xi) - Q_{\text{bought}}^{\text{actual}} = 0 \). By the implicit function theorem, we have:
\[
\frac{\partial \xi_t}{\partial Q_{\text{actual bought}}} = -\frac{-1}{\sum_k M_k, t s^k_{\text{buy}}(S, \xi)}
\]  

Through the same steps, we can find that this equals:

\[
\frac{\partial \xi}{\partial Q_{\text{actual bought}}} = -\sum_k M_k (1 - s^k_{\text{buy}}(S, \xi)) * s^k_{\text{buy}}(S, \xi)
\]  

\[\text{(45)}\]

C Market Sizes

The video game industry is a two-sided market - individuals must first buy a console (i.e. hardware) before they can play any games (software) for that console. Therefore, it is natural for the market size of a game to be comprised of two components: one for the initial market size and another for the market size growth each period due to entry of new consumers.

Using observed cumulative console sales for the market size generates two problems in this context. First, when including all console buyers, the share of the market buying a game in a month is very small; it average is 0.0004 in 1st 12 months following a games release. As a result, including all console owners yields odd results. For example, the small share buying each period would only do so due to large transient shocks, and thus most buyers would want to resell as soon as possible unless utility derived from use increased very quickly between the first and second period’s of use. This clearly does not happen – used sales in a period are not proportional to the total sales and the prior period.

Second, assuming that new and old console owners are equally likely to be in the market for games is inconsistent with the data. Assuming that this is true would imply that games released later in a console’s lifecycle should have very different sales and price paths over time than games released early in a console’s lifecycle, since the number of incoming console owners relative to the cumulative number of consoles purchases declines substantially over time (it averages 0.24 in the 1st year, 0.070 in the 2nd, and 0.039 in the 3rd). In fact, the price and sales path’s of games differ very little across release dates. Thus, it seems likely that older console owners are not as likely to be in the market for a particular game as new console owners.

To address both concerns, I estimate the market-size for games. I assume that the market size for a game is comprised of three components: the initial market size, consumers exiting the market after buying, and the incoming market size. Assuming that the last component is constant across periods for a specific game, the market size for game \( j \) equals:
\[ M_{j,t} = \text{Initial}_\_MS_j + \text{Game}_\_Age_t \times (\text{Incoming}_\_MS_j) - \text{Cumulative}_\_Buyers_{j,t} \quad (46) \]

I estimate the components of the market size under the additional assumption that nearly all consumers in the market would buy a game once the price has leveled off at around $6. After leveling off, the number of buyers each period simply equals the number of incoming potential consumers each period that value the discounted use of the product above $6. After finding the incoming consumers market size, the initial market size that values the product above $6 can then be computed as the number of consumers that bought minus the total number of incoming potential consumers.

Since games were released at different times and I cannot readily observe the amount to which sales plateau to for every game, I estimate it and the number of initial sales by fitting the sales of game over time to the exponential function with a nonzero plateau by minimizing the sum of squared error. Specifically, I assume that the sales of a game in period \( t \) equals:

\[
\bar{Q}_j(t) = a_j \times \exp(b_j \times (t - r)) + (c_1 + c_2 \times r_j)
\]

(47)

where \( a_j \) and \( b_j \) are game specific parameters, \( c_1 + c_2 \) are parameters constant across games, and \( r_j \) is the release date of game \( j \). The parameter \( a_j \) allows for different games to have different sales in early periods, and the term \( b_j \) allows for sales to drop off at different rates, for example to different rates of price declines. The incoming group of potential consumers each period for game \( j \), \( \text{Incoming}_\_MS_j \), simply equals \( (c_1 + c_2 \times r_j) \). The initial installed base, \( M_{j,1} \), then equals the \( \int_{t=0}^{\infty} a_j \times \exp(b_j \times (t - r)) \, dt \).

### D  Deseasoning the Data

There are several times of the year in which games tend to sell more, for example, during Christmas. One method for controlling for seasonality is to add monthly demand shifters. However, Gowrisankaran and Rysman (2010) point out the lack of intuition for why products would be enjoyed so much more during the Christmas season, and that adding season dummies to a dynamic model typically requires adding an additional state variable, substantially slowing estimation due to the curse of dimensionality. Another method of accounting for seasonality is deseasoning the data prior to estimation. Gowrisankaran and Rysman (2010) show that these two methods yield roughly the same parameter estimates for the other parameters in the model. Given that the model already takes a very long time to
estimate without season dummies and that the two methods have been shown to be roughly equivalent, the deseasoning approach is used.

The data are deseasoned by running a regression of the log of the dependent variable in a period on the composite critic review score and its square, age of game dummies, and date fixed fixed. Specifically:

\[
\log(Dependent_t) = \alpha + \beta_1 \times rev\_score_j + \beta_2 \times rev\_score_j^2 + \lambda_{age(t)} \times I(age(t)) + \gamma_t \times I(t) + \varepsilon_t
\]  

(48)

The dependent variable is deseasoned by subtracting \(\gamma_t \times I(t)\) from the log of the dependent variable, and then exponentiating. This variable is then scaled up or down to the point where the sum of this seasonally adjusted variable equals the sum of the corresponding raw, (not deseasoned) variable. This process is repeated for prices, new quantities, and used quantities.

**E Technical Details**

As there is no closed form solution to the value function, it must be estimated numerically. Blackwell’s Theorem can be used to show that the Bellman equation in this model is a contraction. I estimated it for a grid of prices, and used linear interpolation for points in between. A fine grid for price was needed for convergence.
<table>
<thead>
<tr>
<th>Age (in Months)</th>
<th>Quantity</th>
<th>Price</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>New</td>
<td>Used</td>
</tr>
<tr>
<td></td>
<td>Mean</td>
<td>SD</td>
</tr>
<tr>
<td>1</td>
<td>22.1</td>
<td>12.8</td>
</tr>
<tr>
<td>2</td>
<td>17.4</td>
<td>9.7</td>
</tr>
<tr>
<td>3</td>
<td>9.2</td>
<td>6.7</td>
</tr>
<tr>
<td>4</td>
<td>7.7</td>
<td>5.9</td>
</tr>
<tr>
<td>5</td>
<td>5.0</td>
<td>2.8</td>
</tr>
<tr>
<td>6</td>
<td>4.4</td>
<td>3.2</td>
</tr>
<tr>
<td>7</td>
<td>4.0</td>
<td>4.6</td>
</tr>
<tr>
<td>8</td>
<td>3.2</td>
<td>3.1</td>
</tr>
<tr>
<td>9</td>
<td>2.7</td>
<td>2.0</td>
</tr>
<tr>
<td>10</td>
<td>2.8</td>
<td>2.9</td>
</tr>
<tr>
<td>11</td>
<td>2.2</td>
<td>1.8</td>
</tr>
<tr>
<td>12</td>
<td>1.9</td>
<td>1.7</td>
</tr>
</tbody>
</table>

*Normalized by total sales (new and used) in the first 12 months, by game.*
Table 2
Regression of Ratio of Cumulative Secondhand Sales to New Sales on Game Characteristics

<table>
<thead>
<tr>
<th></th>
<th>Dependent Variable is Q(used)/Q(new)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1</td>
</tr>
<tr>
<td>Game Age (in Months)</td>
<td>0.0126**</td>
</tr>
<tr>
<td></td>
<td>(0.0007)</td>
</tr>
<tr>
<td>Review Score</td>
<td>0.0010</td>
</tr>
<tr>
<td></td>
<td>(0.0006)</td>
</tr>
<tr>
<td>Game Informer Replay Value</td>
<td></td>
</tr>
<tr>
<td>Moderately Low</td>
<td>-0.0038</td>
</tr>
<tr>
<td></td>
<td>(0.0621)</td>
</tr>
<tr>
<td>Moderate</td>
<td>0.0100</td>
</tr>
<tr>
<td></td>
<td>(0.0511)</td>
</tr>
<tr>
<td>Moderately High</td>
<td>0.0313</td>
</tr>
<tr>
<td></td>
<td>(0.0504)</td>
</tr>
<tr>
<td>High</td>
<td>0.0050</td>
</tr>
<tr>
<td></td>
<td>(0.0503)</td>
</tr>
<tr>
<td>ESRB rating</td>
<td></td>
</tr>
<tr>
<td>Teen</td>
<td>0.0001</td>
</tr>
<tr>
<td></td>
<td>(0.0171)</td>
</tr>
<tr>
<td>Mature</td>
<td>0.0289</td>
</tr>
<tr>
<td></td>
<td>(0.0197)</td>
</tr>
<tr>
<td>Constant</td>
<td>0.0619**</td>
</tr>
<tr>
<td></td>
<td>(0.1325)</td>
</tr>
<tr>
<td>Observations</td>
<td>323</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.49</td>
</tr>
</tbody>
</table>

Standard errors in parentheses.
** denotes significance at 5% level
Table 3
Price Path Regressions

<table>
<thead>
<tr>
<th></th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
</tr>
</thead>
<tbody>
<tr>
<td>P(t-1)</td>
<td>0.962**</td>
<td>0.960**</td>
<td>0.955**</td>
<td>0.955**</td>
<td>0.955**</td>
<td>0.95**</td>
</tr>
<tr>
<td></td>
<td>(0.006)</td>
<td>(0.021)</td>
<td>(0.007)</td>
<td>(0.007)</td>
<td>(0.007)</td>
<td>(0.007)</td>
</tr>
<tr>
<td>P(t-2)</td>
<td>-0.006</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.022)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2nd Critic Quintile</td>
<td>-0.157</td>
<td>-0.135</td>
<td>-0.162</td>
<td>-0.162</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.319)</td>
<td>(0.316)</td>
<td>(0.340)</td>
<td>(0.321)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>3rd Critic Quintile</td>
<td>-0.107</td>
<td>-0.106</td>
<td>-0.178</td>
<td>-0.106</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.333)</td>
<td>(0.330)</td>
<td>(0.341)</td>
<td>(0.347)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>4th Critic Quintile</td>
<td>0.084</td>
<td>0.093</td>
<td>0.055</td>
<td>0.159</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.324)</td>
<td>(0.321)</td>
<td>(0.336)</td>
<td>(0.332)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>5th (Highest) Critic Quintile</td>
<td>1.058**</td>
<td>1.063**</td>
<td>0.946**</td>
<td>1.075**</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.364)</td>
<td>(0.361)</td>
<td>(0.379)</td>
<td>(0.379)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Month FE</td>
<td>Yes**</td>
<td>Yes**</td>
<td>Yes**</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>[0.000]</td>
<td>[0.000]</td>
<td>[0.000]</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Release Month</td>
<td>Yes</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>[0.920]</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Genre</td>
<td>Yes</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>[0.584]</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>-0.801**</td>
<td>-0.587</td>
<td>-0.625</td>
<td>-0.557</td>
<td>-0.933</td>
<td>-0.489</td>
</tr>
<tr>
<td></td>
<td>(0.299)</td>
<td>(0.335)</td>
<td>(0.348)</td>
<td>(0.488)</td>
<td>(0.775)</td>
<td>(0.518)</td>
</tr>
<tr>
<td>Observations</td>
<td>2423</td>
<td>2202</td>
<td>2346</td>
<td>2346</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>2313</td>
<td>2346</td>
<td>2346</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>R-squared</td>
<td>0.906</td>
<td>0.901</td>
<td>0.906</td>
<td>0.908</td>
<td>0.908</td>
<td>0.908</td>
</tr>
</tbody>
</table>

Standard errors in parentheses.
F-statistics in brackets
** denotes significance at 5% level
Regression includes prices in first 12 months for XBOX 360 games released prior to December, 2007 (i.e. games with at least 12 months in dataset).
### Table 4

**Estimation Results**

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
<th>Standard Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rate of Tiring Coef 1</td>
<td>$\lambda_1$</td>
<td>-1.0</td>
</tr>
<tr>
<td>Rate of Tiring Coef 2</td>
<td>$\lambda_2$</td>
<td>0.74</td>
</tr>
<tr>
<td>Hard-core Gamers Additional Value</td>
<td>$\beta$</td>
<td>7.91</td>
</tr>
<tr>
<td>Fraction Hard-Core Gamers</td>
<td>$\gamma$</td>
<td>0.69</td>
</tr>
<tr>
<td>Stand. Dev. (Demand Shock)</td>
<td>$\sigma(\xi)$</td>
<td>1.70</td>
</tr>
<tr>
<td>Stand. Dev. (Trans. Cost Shock)</td>
<td>$\sigma(\zeta)$</td>
<td>18.2</td>
</tr>
<tr>
<td>Correlation Btw Demand and Supply Shocks</td>
<td>$\rho_{\xi,\eta}$</td>
<td>0.50</td>
</tr>
<tr>
<td>Price Sensitivity</td>
<td>$\alpha$</td>
<td>0.52</td>
</tr>
</tbody>
</table>

Game fixed effects, not reported above, averaged about 22 above $\omega$. Their point estimates had a standard deviation of 3.42.
### Table 5

**Mean Price Elasticity Estimates**

<table>
<thead>
<tr>
<th>Age of Game in Month</th>
<th>Static</th>
<th>Dynamic (3 Month Q)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$Q_{new}$</td>
<td>$Q_{total}$</td>
</tr>
<tr>
<td>1</td>
<td>-1.90</td>
<td>-1.90</td>
</tr>
<tr>
<td></td>
<td>(0.70)</td>
<td>(0.70)</td>
</tr>
<tr>
<td>2</td>
<td>-3.36</td>
<td>-2.41</td>
</tr>
<tr>
<td></td>
<td>(0.78)</td>
<td>(0.58)</td>
</tr>
<tr>
<td>3</td>
<td>-4.25</td>
<td>-2.52</td>
</tr>
<tr>
<td></td>
<td>(1.62)</td>
<td>(0.85)</td>
</tr>
<tr>
<td>4</td>
<td>-5.56</td>
<td>-2.38</td>
</tr>
<tr>
<td></td>
<td>(3.07)</td>
<td>(0.76)</td>
</tr>
<tr>
<td>5</td>
<td>-6.20</td>
<td>-2.24</td>
</tr>
<tr>
<td></td>
<td>(4.24)</td>
<td>(0.78)</td>
</tr>
<tr>
<td>6</td>
<td>-6.55</td>
<td>-2.15</td>
</tr>
<tr>
<td></td>
<td>(4.15)</td>
<td>(0.85)</td>
</tr>
<tr>
<td>7</td>
<td>-7.03</td>
<td>-2.15</td>
</tr>
<tr>
<td></td>
<td>(4.58)</td>
<td>(0.84)</td>
</tr>
<tr>
<td>8</td>
<td>-7.39</td>
<td>-2.03</td>
</tr>
<tr>
<td></td>
<td>(4.12)</td>
<td>(0.91)</td>
</tr>
<tr>
<td>9</td>
<td>-6.90</td>
<td>-1.86</td>
</tr>
<tr>
<td></td>
<td>(4.79)</td>
<td>(0.93)</td>
</tr>
<tr>
<td>10</td>
<td>-6.17</td>
<td>-1.73</td>
</tr>
<tr>
<td></td>
<td>(3.19)</td>
<td>(0.94)</td>
</tr>
<tr>
<td>11</td>
<td>-5.54</td>
<td>-1.56</td>
</tr>
<tr>
<td></td>
<td>(2.49)</td>
<td>(1.01)</td>
</tr>
</tbody>
</table>

Standard deviations of point estimates across games in parentheses.

Both types of elasticities allow consumers to update beliefs of future prices.

The dynamic elasticities show the percent change in the quantity bought in the subsequent three months for a percent change in the current price.
Table 6  
Counterfactual Results

<table>
<thead>
<tr>
<th></th>
<th>Allowed Resale†</th>
<th>Prohibited Resale</th>
</tr>
</thead>
<tbody>
<tr>
<td>Producer Profits (in millions)</td>
<td>$40.5</td>
<td>$91.1</td>
</tr>
<tr>
<td>Revenue from Consumer Resale‡ (in Millions)</td>
<td>$8.19</td>
<td>N/A</td>
</tr>
<tr>
<td>Quantity of New Goods Sold (in millions)</td>
<td>0.945</td>
<td>3.51</td>
</tr>
<tr>
<td>Quantity of Used Goods Resold (in hundreds of thousands)</td>
<td>0.297</td>
<td>N/A</td>
</tr>
</tbody>
</table>

*First Twelve Months Post Release
†Numbers for allowed resale are computed using observed sales.
‡Equals amount received by consumers reselling games.
Table 7

Nested Logit Estimation of Substitutability

<table>
<thead>
<tr>
<th>Dependent Variable is $\log(s_{jt}/s_{0t})$</th>
<th>OLS</th>
<th>2SLS</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age ($t - r_j$)</td>
<td>-0.194</td>
<td>-0.317</td>
</tr>
<tr>
<td></td>
<td>(0.007)</td>
<td>(0.015)</td>
</tr>
<tr>
<td>Age$^2$</td>
<td>0.009</td>
<td>0.025</td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
<td>(0.006)</td>
</tr>
<tr>
<td>Age$^3$</td>
<td>-0.001</td>
<td>-0.003</td>
</tr>
<tr>
<td></td>
<td>(0.000)</td>
<td>(0.000)</td>
</tr>
<tr>
<td>Price</td>
<td>-0.012</td>
<td>-0.013</td>
</tr>
<tr>
<td></td>
<td>(0.002)</td>
<td>(0.002)</td>
</tr>
<tr>
<td>Within Genre Share ($\sigma$)</td>
<td>0.623</td>
<td>0.602</td>
</tr>
<tr>
<td></td>
<td>(0.014)</td>
<td>(0.014)</td>
</tr>
<tr>
<td>Observations</td>
<td>2875</td>
<td>2875</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.93</td>
<td>0.93</td>
</tr>
</tbody>
</table>

Notes: Standard errors in parentheses. Game and month fixed effects are included in all specifications. Regression restricted to observations where the game’s age ($t - r_j$) $\leq$ 12. Regressions of endogenous variables on instrument matrix: prices: (Rsquare = 0.92, F = 27975), within genre share (Rsquare = 0.55, F = 3220).
Figure 1

Plot of the Ratio of Quantity Used Sold to Quantity New Sold Against Game Age as of Dec 2008

Q(used)/Q(new)

Age of Game (in Months) in Final Period

Points jittered
Box-Plot the Absolute Value of the Residuals of a Regression of $Q(\text{new})/Q(\text{used})$ on Game Age, Over New Sales Deciles
Figure 3

![Graph showing Flow Value of Use (Rel. to Outside Value) over Previous Ownership Periods for Low Type (Mass Market) and High Type (Hardcore).]
Figure 4 A
Plot of Demand Shocks Across Time

Figure 4 B
Plot of Transaction Cost Shocks Across Time
Figure 5
Price Path Over Time Under Different Legal Environments

![Price Path Over Time Under Different Legal Environments](image-url)